# River Temperature Forecasting: A Coupled-Modeling Framework for Management of River Habitat

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***Abstract*—Humans have substantially altered the thermal regimes of freshwater habitats worldwide, with significant environmental consequences. There is a critical need for a comprehensive modeling framework for forecasting the downstream impacts of two of the most common anthropogenic structures that alter river water temperatures: 1) dams that selectively release water from thermally stratified reservoirs, and 2) power generating stations and industrial plants that use river water for once-through cooling. These facilities change the thermal dynamics of the downstream waters through a complex interaction of water release volume and temperature and the subsequent exchange with the environment downstream. In order to stay within the downstream temperature limits imposed by regulatory agencies, managers must monitor not just release volumes and temperatures, but also need to be able to forecast the thermal impacts of their day-to-day operations on habitat which may be hundreds of kilometers downstream. Here we describe a coupled modeling framework that links mesoscale weather and ecological models to generate inputs for a physically-based water temperature model for monitoring and forecasting river temperatures downstream from these facilities at fine spatiotemporal scales. We provide an example of how this modeling framework is being applied to a water allocation decision support system (DSS) for the management of Endangered Species Act (ESA) listed salmon species in the Sacramento River in California.**

***Index Terms*—Forecasting, water resources.**

## I. Introduction

THE management of freshwater resources is one of the greatest challenges currently facing society. With increasing demand for water, alteration of river systems (through dams, channelization, and diversions), and a changing climate, humans are altering the water temperature regimes of riverine habitats throughout the world. The thermal impacts of these changes on the ecology of river ecosystems have been well documented [1]–[5]. Two common anthropogenic structures that impact thousands of rivers worldwide are: 1) dams and 2) power generating stations and industrial plants that use river water for once-through cooling; (both types of structures are hereafter referred to as "temperature altering facilities" or TAFs). Dams can alter downstream thermal regimes by causing a lag in the amount and temperature of the water stored behind the reservoir, and also by the selective release of warm or cold water from thermally stratified reservoirs. Power plants and industrial facilities remove water from a river and pass it through steam condensers, substantially increase the temperature in the process, and return the water to the river. In the United States alone there are 6,294 dams $>15$ m in height [6], and 1,260 power plants and industrial facilities that each use at least 2 million gallons of cooling water per day [7].

To protect the thermal habitat downstream from TAFs, regulatory agencies set temperature limits for specific compliance points downstream. Managers then adjust the operations of the TAFs to control the volume and the temperature of the discharged water in an effort to stay within these limits, typically employing a temperature observing-modeling framework to inform their decisions. Outflow temperatures and volumes are typically measured at the point of release from the TAFs, allowing for evaluation of impacts immediately downstream. However, this presents a significant challenge when the compliance point is some distance downstream from the discharge because of the loss of direct feedback; (it may take days for water to travel from the discharge to the compliance point) [8]. In these situations the downstream target temperature is a complex function of the interaction of release volume, release temperature, and the subsequent heat exchange between the river and the environment. In addition, water temperature compliance standards may vary among management agencies, requiring specialized models to inform decision support systems [9]. This has resulted in a diverse array of water temperature models that vary widely in scope, resolution, and complexity [1].

Much of the literature on water temperature modeling is focused on developing the quantitative tools, using statistical and/or physically-based methods, to reproduce observed water temperatures [10]. Relatively little research has been focused on linking mesoscale weather models and water temperature models to generate accurate real-time forecasts. The latter requires adapting existing water temperature models to account

Manuscript received October 14, 2011; revised April 26, 2012 and August 10, 2012; accepted October 26, 2012. Date of publication December 03, 2012; date of current version December 28, 2012. This work was supported in part by NASA Applied Sciences Program's Ecological Forecasting Program Element (grant NNX08AK72G) and the NOAA/NMFS Southwest Fisheries Science Center.

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Digital Object Identifier 10.1109/JSTARS.2012.2229968

for error propagation that arises when coupling sensitive parameters among models [11], [12].

What is needed is a modeling framework that is capable of taking advantage of the significant recent advances in accurate river heat budget models [13] and spatially explicit weather forecasting models [14] to accurately predict the temperature dynamics of water after it is released from a TAF. This modeling framework would couple these models to produce accurate river temperature forecasts at mesoscales (sub-hourly at 1 km) for downstream waters, using the TAF discharge temperature and flow as boundary conditions. Note that this framework would not evaluate how individual TAFs alter the temperature between intake and outflow, which is highly specific to each structure. The framework would inform TAF managers of the predicted temperature regimes under current operations, and allow managers to quantitatively evaluate a range of alternative operating scenarios.

Here we describe a coupled modeling framework that links mesoscale weather and ecological models to generate inputs for a physically based water temperature model for forecasting river temperatures downstream from TAFs at fine spatiotemporal scales. While this framework was specifically developed for regulated rivers with dams (where the upstream thermal releases are controllable), it can be applied to rivers with other anthropogenic cooling structures (power plants and industrial plants), and also to rivers without these structures, to accurately model the thermal landscape. We describe how this modeling framework is being applied to a water temperature decision support system (DSS) for the Shasta Dam for the management of Endangered Species Act (ESA) listed salmon species in the Sacramento River in California. Because this modeling framework operates in a distributed environment and relies on web services to link the operation of models from different domains to provide a new forecasting capability, we also discuss implications for the future development of model webs [15].

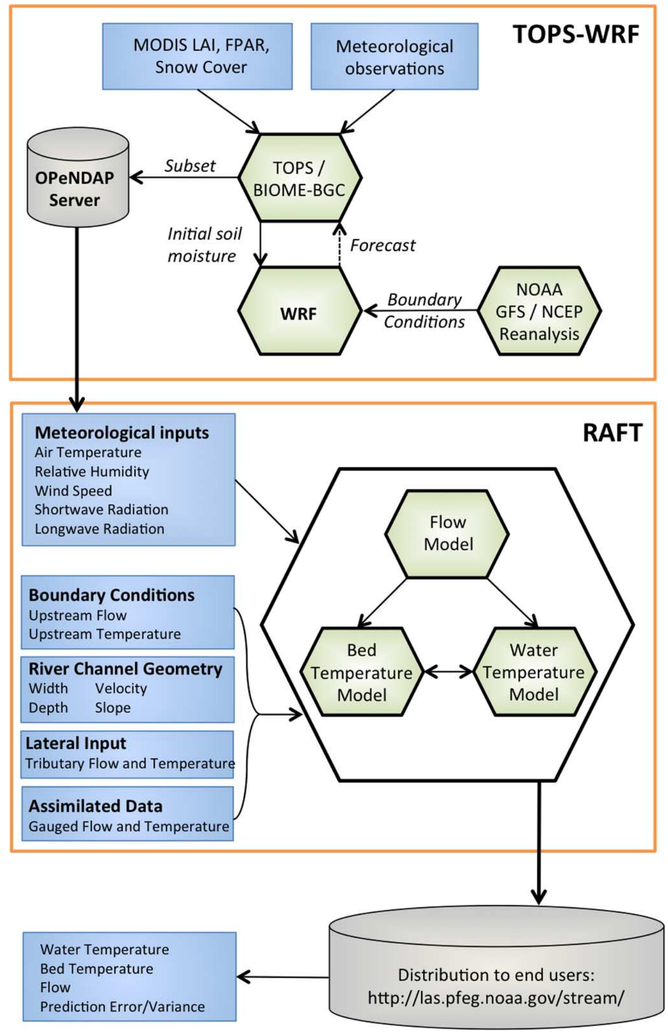


Fig. 1. The coupled modeling framework. A mesoscale weather model, the Weather Research and Forecasting (WRF) model, Biome-BGC, an ecological component model of the Terrestrial Observation and Prediction System (TOPS) are linked to form TOPS-WRF. This provides the necessary input data into the physically based water temperature model, the River Assessment for Forecasting Temperatures (RAFT) model. The outputs from RAFT are distributed to the end-users through web services and an interactive web site.

## II. Methods

### A. Integrated River Temperature Modeling Framework

The coupled modeling framework links two main components: 1) a mesoscale weather model, which consists of the Weather Research and Forecasting (WRF) model coupled with Biome-BGC, an ecological component model of the Terrestrial Observation and Prediction System (TOPS), henceforth referred to as TOPS-WRF, and 2) a physically based water temperature model, the River Assessment for Forecasting Temperatures (RAFT, [16]) model (Fig. 1). This integrated framework combines high-quality environmental input data into a data assimilation model that includes a suite of characteristics that are not present in any other single river temperature model: 1) a high degree of accuracy, 2) high spatial and temporal resolution (1 km and at sub-hourly intervals), 3) a predictive capability with a multi-day forecasting range, 4) physically based to handle a range of conditions, and 5) propagation of error and assessment of uncertainty.

### B. RAFT

The RAFT model is based on a heat budget model for predicting the downstream thermal impacts of reservoir operations [16]. The model computes rates of heat transfer to/from the river based on weather conditions, while also calculating internal heat movement within the river due to hydrodynamic transport. Heat exchange due to insolation, conduction, and evaporation are all explicitly included in the model. RAFT extends a state-space model developed for predicting impacts of thermal effluent from power plant operations [8] by including spatially variable meteorology, inputs/outputs from tributaries and water withdrawals, and dynamic flow conditions. The state-space formulation allows assimilation of available real-time temperature data and estimation of uncertainty in model predictions. Given adequate inputs, real-time forecasts of water temperature can be issued up to 72 hours into the future.

The input requirements of RAFT are typically available for regulated rivers in the United States. These include temperature and flow measurements at the reservoir outflow and incoming tributaries, river channel geometry, and gridded meteorological predictions (Fig. 1). Real-time water temperature and flow are monitored by federal and state agencies at the outflow of most dams and at multiple sites downstream. Channel geometry data are increasingly available for many rivers due to improvement in high-resolution surveying technology, such as acoustic profiling and bathymetric LIDAR. Lastly, gridded meteorological data are provided by coupling outputs from the TOPS-WRF ecosystem model driven with satellite observations of land surface conditions with numerical weather modeling. Whereas most water temperature models are parameterized by data from a few nearby meteorological stations, RAFT utilizes gridded meteorological inputs to substantially improve the spatial and temporal resolution of water temperature predictions.

In addition to meteorology, RAFT considers non-linear interactions between flow, water temperature, and streambed temperature. Flow affects both the travel time of water and the thermal mass of the river, such that lower flows result in increased heat exchange with the environment. In summer months, reduced flows lead to warmer river temperatures. Furthermore, the water column and streambed exchange heat. The streambed absorbs a fraction of incoming solar radiation and slowly releases this heat into the water column. Heat exchange between the two tends to buffer the water column from high-magnitude swings in temperature throughout the day. To account for these effects, RAFT couples an unsteady non-uniform flow routing model and streambed temperature model with standard water temperature formulations.

RAFT estimates uncertainty in predictions by considering the governing equations of heat flow as a stochastic dynamic system, where water temperature is treated as a random variable that is subject to error. By transforming the system dynamics into a particular algebraic form known as a state-space model, the predicted state (water temperature) is reduced to a linear function of the previous state and model inputs. Both the process-based model and observations are subject to error due to uncertainty in atmospheric inputs, model processes, and measurement error. Using the Kalman Filter (a data-assimilation algorithm), the process-based estimates are combined with observations, based on their relative uncertainty, to produce an optimal state estimate. Error variance is routed through the system so that dynamic confidence bands of prediction error can be simultaneously computed with the state and included in the model output.

### C. TOPS-WRF

To generate the required meteorological inputs for the RAFT model, we leveraged capabilities provided by TOPS [17], [18]. TOPS is a modeling and data assimilation framework that integrates observations from satellites and surface sensor networks with ecological models and numerical weather and climate models to produce forecasts of ecological conditions. TOPS currently uses data from multiple satellite sensors (e.g., MODIS, Landsat TM/ETM+, AVHRR, and AMSR-E), multiple meteorological station networks in the U.S. (e.g., NOAA Cooperative Observer Program stations and agricultural weather networks such as the California Irrigation Management Information System), and ancillary data sources (e.g., the National Elevation Dataset, and the USDA U.S. General Soil Map [STATSGO2]). To provide a short-term forecasting capability, the Weather Research and Forecasting (WRF) model (Advance Research WRF, version 3.1.1) has been integrated into TOPS. WRF is a mesoscale numerical weather model designed to support both research and operational forecasting, providing estimates of hundreds of atmospheric and land surface parameters, and its software architecture provides for computational parallelism [14]. This feature of WRF can greatly reduce run-time (in total elapsed time), which is important for time-sensitive applications, such as the application of the RAFT model for water allocation decisions (see Application of the modeling framework to manage ESA listed salmon below).

One limitation of weather forecasting models is that they have been shown to exhibit a sensitivity to land surface conditions, particularly soil moisture, and the lack of these observations has been a persistent problem. One of the key advantages of integrating WRF with TOPS is that soil moisture estimates from TOPS, which are produced using a well-calibrated ecosystem model (Biome-BGC, [19]) that incorporates satellite observations of current vegetation conditions, can be used to initialize each WRF forecast run. Biome-BGC is a physically based biogeochemical cycle model that simulates fluxes and storage of energy, water, carbon, and nitrogen for terrestrial ecosystems, and the model captures a range of processes, from sunlight interception, photosynthetic fixation of carbon, and leaf growth, to snow accumulation and melt, and decomposition of plant litter and soil organic matter [19]. Biome-BGC uses a daily time step and requires spatially continuous gridded meteorological surfaces as inputs. Within TOPS, Biome-BGC is run in both diagnostic and prognostic modes. In its diagnostic mode, the model directly ingests estimates of leaf area index (LAI) and fraction of photosynthetically active radiation (FPAR) from satellite observations to produce estimates of photosynthesis and evapotranspiration. In its prognostic mode, the model dynamically simulates vegetation growth and carbon/nitrogen cycles and thus extrapolates current ecosystem states into the future [17]. The approach used in TOPS to couple the ecological models and numerical weather models is conceptually similar to that used in the NASA Land Information System [20], and provides an improved capability for forecasting surface meteorological conditions and cloud formation that is driven in part by satellite observations of current vegetation conditions. Integration of TOPS with WRF also facilitates customized mesoscale weather forecasting to meet the input requirements for other models, such as the very high spatial resolutions ($<=3$ km grid cell lengths) required by the RAFT model.

To generate retrospective forecasts (hindcasts), TOPS-WRF is driven with satellite observations of LAI and FPAR (MOD15A2) from the MODIS instrument onboard the Terra satellite and atmospheric boundary conditions from the NOAA National Centers for Environmental Prediction (NCEP/NCAR) Reanalysis data [21]. The NOAA NCEP/NCAR Reanalysis project provides data on atmospheric conditions from 1948 to present at a 6-hour interval. For operational forecasts, TOPS-WRF relies on the NOAA Global Forecasting System (GFS) high-resolution (1 degree) data to parameterize the regional runs and set the boundary conditions. The NOAA GFS data are available from NOAA via the NOAA Operational Model Archive and Distribution System (NOMADS). TOPS-WRF is then used to produce the regional forecast data for each 72-hour period at an hourly time step using nested grids at spatial resolutions of 27 km, 9 km, and 3 km. Hourly data are linearly interpolated to a 15-minute interval to match the input requirements for the RAFT model.

Outputs from the TOPS-WRF coupled modeling framework that were used to drive the RAFT model in both hindcast and forecast mode included all the necessary meteorological parameters (Fig. 1). Data relay between TOPS-WRF and the RAFT model is accomplished via an OPeNDAP data service (Open-source Project for a Network Data Access Protocol [22]). OPeNDAP provides remote access to NetCDF and HDF format archives and facilitates access, subsetting, and customized data retrieval from multiple clients. This framework allows the components of the integrated modeling framework to run on the same server, or over the network via a set of data services that allow the remote components to remain tightly coupled. For both retrospective and operational forecasts, TOPS-WRF 72-hour forecasts were updated every six hours and ingested by the RAFT model, along with the most recent hourly observations of outflow temperatures from the USGS gauges, to produce forecasts of river temperature every 15 minutes for every 1 km length of river.

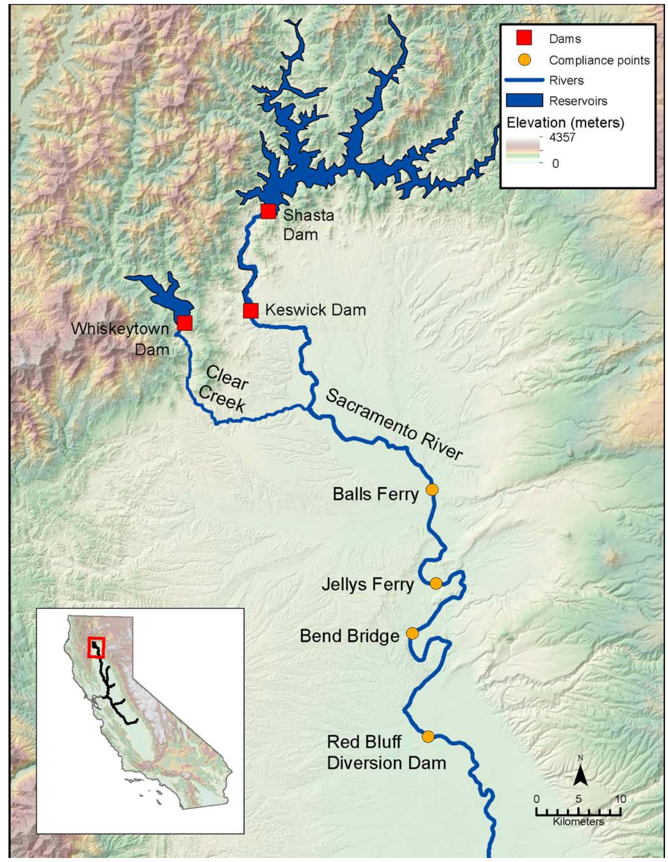


Fig. 2. The study area on the Sacramento River for the application of the modeling framework to manage ESA listed salmon. Water is released from Shasta Dam and subsequently regulated by Keswick Dam. Managers attempt to maintain water temperatures below 13.3°C at as many of the compliance points (orange circles) downstream as possible. RAFT incorporates lateral inputs from tributaries such as Clear Creek.

## III. Application of the Modeling Framework to Manage ESA Listed Salmon

We applied the coupled modeling framework to a decision support system for water operations on the Sacramento River in California's Central Valley. This system provides an ideal test case because the Sacramento River supports four runs (populations) of thermally sensitive Chinook salmon, which require cold water for spawning, development, and growth. The construction of Shasta Dam, and later Keswick Dam approximately 7 km downstream (Fig. 2), blocked access for these fish to their ancestral cold-water spawning habitat in the high-elevation tributaries of the southern Cascade Range, and the fish are now forced to spawn and rear in the mainstem of the Sacramento River in the northern end of the Central Valley. In the late summer and fall, water temperatures in the upper portions of the Sacramento River can exceed critical thresholds, having lethal and sublethal impacts on salmon eggs and juveniles. To protect these ESA listed salmon, federal and state regulations [23] require that dam operations release enough cold water during the period of highest thermal stress (July to October) to maintain temperatures downstream of Keswick Dam below 13.3°C at a series of compliance points: Balls Ferry (42 km), Jellys Ferry (57 km), Bend Bridge (73 km), and Red Bluff (97 km) (Fig. 2). Water managers attempt to meet these criteria by regulating the temperature and volume of water released from Shasta Dam. Without a forecasting model such as RAFT, operators cannot accurately predict the downstream temperature dynamics and rely instead on weekly mean temperature estimates, which do not capture the significant diel temperature variation that occurs on the Sacramento River. Use of temperature estimates for a limited number of locations may also mask impacts to critical habitat between compliance points, whereas RAFT is capable of providing forecasts for the entire river at a spatial resolution of 1 km.

We applied the modeling framework in real-time using the initial water temperature and flow data collected by the US Geological Survey (USGS) at the outflow from Keswick Dam, with flow and temperature data assimilation at the four gauged compliance points. The stream morphology and information on channel width and depth were obtained from the CA Department of Water Resources (CA DWR, 2002). The channel bathymetry is characterized by a series of channel cross-sections spaced sporadically (~500 m apart) along the length of the main stem of the Upper Sacramento River. Using a hydrologic routing model [24], we performed a suite of steady-flow simulations to compute channel geometry characteristics (width, depth, and velocity) at each cross-section for varying flow rates. RAFT outputs 2-dimensional filled contour plots showing predicted river temperatures in time

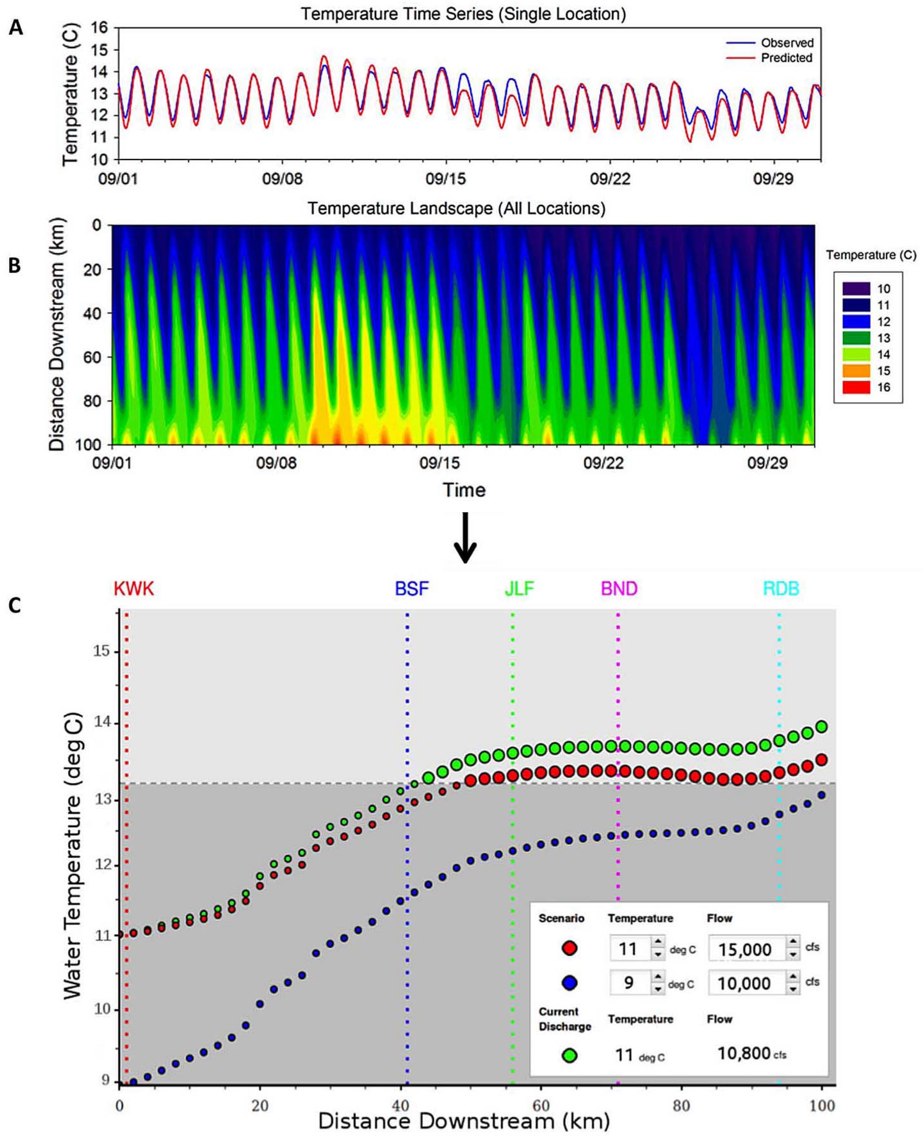


Fig. 3. Examples of the RAFT outputs and data distribution web site. a) Model predictions (red) and observed values (blue) at the first compliance point (Balls Ferry). Note that the model captures the diel variation in water temperature; b) Model output includes the entire "temperature landscape", a shaded contour plot depicting river temperature time-series for all locations; and c) A dynamic website that allows end-users to run customized reservoir-release scenarios and visualize the predicted downstream impacts. Users will be able to create graphs such as the one shown to visualize the modeled temperatures for the current operating conditions (in this example for Sept 9, 2011, in green), and two alternative scenarios. The above shows one scenario with similar release temperature but increased flow (red), and another with similar flow but decreased release temperature (blue).

(15 min) and space (1 km) over the course of a week (Fig. 3(a)). A horizontal slice through this plot is akin to a time-series at one location, whereas a vertical slice denotes a longitudinal temperature profile at a single point in time. We refer to this plot as a "temperature landscape", as it is able to compactly display the temperature history of the entire river (9600 points per day). Two main patterns are evident. First, water temperature generally increases with distance downstream from the dam. Second, diel variation in water temperatures occurs at all locations, although the magnitude of diel variation as well as the timing of the minimum and maximum temperatures vary.

The model accuracy assessment and validation process is described in detail in Pike *et al.* [16] and briefly summarized here. Model accuracy was assessed by comparing predicted river temperatures against observed river temperatures at the four gauged compliance points. For the test period (May–November 2010) when river temperatures ranged from 9.5°C to 16.6°C, the root mean squared error of predictions ranged between 0.15°C to 0.75°C, depending on the location downstream of the dam. When intermediate gauge data were assimilated, the maximum uncertainty in predictions was between compliance points, with maximum error of 0.25°C. For forecasting, the one-step prediction error ranged from 0.08°C to 0.15°C. The 72-hour forecast error approached that of the unassimilated model (0.15°C to 0.75°C). This level of accuracy was achieved across a range of discharge scenarios from 5000 cfs to 20,000 cfs, and 8°C to 13.5°C.

## IV. Distributing Data to Users

The coupled modeling framework described here is an important advancement in river temperature forecasting and has significant potential to impact how TAFs are managed. However, to be an effective operational system, data must be readily available to fisheries and water managers via an intuitive data interface. In addition, data should also be available to the regulatory agencies and the larger scientific community via standardized data services that simplify access and allow consistent subsetting, comparison, and integration of a wide variety of model and observational data. We have developed a dynamic web interface, updated in real-time, that provides visual access for water managers to the complete suite of river temperature forecasts. Interactive charts created on-the-fly, along with map-based animations, provide a variety of ways for visualizing and interpreting the data. Through this interface, water and fisheries managers can view the latest 72-hour forecast, compare the observed versus predicted water temperatures for the past season, and run scenarios to evaluate how changes in reservoir releases are likely to affect water temperatures in order to make decisions about future releases. For example, for September 9, 2011, the model forecast indicates that the current operations (11.1°C and 10,800 cfs) will exceed the downstream compliance temperature of 13.3°C starting at river km 40 (green bubbles, Fig. 3(c)). Managers can then view any combination of alternate scenarios, two at a time, along with the current operating conditions. In this example, one scenario has similar release temperature but increased flow (red bubbles, Fig. 3(c)), and the other has similar flow but decreased release temperature (blue bubbles, Fig. 3(c)). In this example, the lower temperature release scenario maintained downstream temperatures below the compliance threshold. Optimal scenarios will depend on the current operating conditions and available resources.

Direct access to each updated forecast for the web interface and for scientific users is provided by a THREDDS (Thematic Realtime Environmental Distributed Data Services) catalog ([25], see also http://www.unidata.ucar.edu/software/tds/). For consistency with standard data protocols, the hourly RAFT model output is stored in NetCDF files ([26], see also http://www.unidata.ucar.edu/software/netcdf/). As each new file is written to the server, THREDDS automatically updates the catalog and makes the new run instantly available to the web interface and other users via OPeNDAP (http://opendap.org/). To further enhance usability, the model output is also served by an ERDDAP (NOAA's Environmental Research Division's Data Access Program) server [27]. ERDDAP provides both graphical and data service capabilities and reformats data into a multitude of formats including common text and application formats, images, and GIS-compatible formats. Both THREDDS and ERDDAP allow users to retrieve data directly into their preferred working environment (MATLAB or R for example) using a RESTful URL (conforming to the REST [representational state transfer] constraints) without downloading entire datasets to their local systems, and without necessarily needing to know the transport mechanism used or the format in which the data were originally stored. Through these services, users can retrieve multiple datasets in common formats for integration and ingestion into other models, such as fish mortality models, or for analysis and inclusion in reports. Together, the web interface and data services fulfill the need for real-time visualization of the forecasts, while facilitating access to the underlying data for use in more detailed analyses.

## V. Discussion

A key component of Integrated Water Resources Management (IWRM) is the protection of aquatic ecosystems for current and future generations [28], [29], and the modeling framework described here can be applied to the thermal evaluation and management of the thousands of rivers impacted worldwide by TAFs. This approach can be applied to any river where the minimum input data are available: upstream boundary temperature and flow, river geometry, and meteorological inputs. The advantages and improvements that the coupled RAFT modeling framework provides over existing temperature models are numerous. First, this model is precise and accurate, on the order of 0.5°C, and even more when downstream temperature observations are assimilated. This high level of accuracy was achieved under a wide range of release flows (5000 cfs to 20,000 cfs) and temperatures (8°C to 13.5°C), validating the capability of RAFT to generate accurate alternate release scenarios (Fig. 3(c)). Second, this model captures important temperature dynamics that occur at finer scales than most models. The sub-hourly river temperature forecasts at a 1 km resolution from the RAFT model are more suitable for evaluating the ecological and physiological impacts on aquatic organisms than existing models that provide mean daily or weekly values [30]. Third, the coupled framework allows for production of temperature estimates across a range of time scales, including multi-year hindcasts, real-time predictions, and forecasts of up to 72 hours. Forecasting is essential for managing water releases from TAFs, where there is no direct feedback control because the downstream water temperature is partially dependent on future weather conditions. Hindcast data are essential for modeling past thermal habitats to assess conditions that may have corresponded with observed changes in aquatic communities or fish populations, and for performing interannual comparisons to assess relative habitat quality or to detect multi-year trends. Finally, the physical nature of the model allows for the quantification of factors that contribute to thermal loading, i.e. the proportional influences of solar radiation and air temperature, allowing for analysis of impacts to river habitat conditions under climate change scenarios.

### *A. Potential for Expansion*

The integrated modeling framework is highly scalable and applicable to rivers in many regions worldwide. In the United States the required static and dynamic inputs for RAFT can be generated for almost any river, and many of the required WRF fields are now operationally produced by NOAA National Weather Service (NWS) regional forecast offices at spatial resolutions of 3–4 km2. While the TOPS-WRF framework, or a similar coupled ecosystem-atmospheric modeling framework, may be required for retrospective testing and validation of the model implementation, it is likely that operational forecasting can be driven by routine NOAA NWS data products, though this may increase uncertainty in river temperature estimates for some regions.

The current framework is well suited to coupling with additional modeling components, which can be easily added to the framework through the ERDDAP web services. For example, models of temperature-dependent fish growth, such as classical bioenergetics [31] and newer dynamic energy budget models [32]–[34], can be adapted to incorporate the high resolution output.

The integrated framework provides the capability to develop long-range forecasts through coupling with statistical methods. Stochastic weather generator (SWG) software can provide multiple realizations of future climate patterns conditioned upon seasonal climate forecasts [35]. The stochastic simulations may then be coupled with RAFT to generate probabilistic measures of river water temperature at lead times of weeks to months. In addition to stochastic weather generation, statistical models may be developed for particular river temperature attributes (e.g., daily temperature range, and number of hours of threshold exceedance). While the spatial and temporal resolution of the statistical methods are somewhat limited relative to the direct RAFT output (i.e., point-specific and generally daily), they substantially increase the lead times beyond the scale of the current framework.

## VI. Conclusion

The integrated modeling framework presented here provides a unique example of the application of mesoscale weather models, ecosystem models, and physically-based hydrologic models to model river temperatures at high spatial and temporal resolutions. The integrated system produces river temperature estimates for every 1 km of river reach at 15-minute intervals, and can forecast these parameters up to 72 hours in advance, making the framework directly applicable to TAF operations with respect to compliance for downstream water temperatures. Data from the modeling framework are distributed to users via a web-based decision support system, which provides both standard visualizations of the data as well as a suite of data services to provide users with direct access to the underlying data for use in further analysis. As RAFT relies on inputs that are increasingly available at the required spatial and temporal resolutions, this framework can also be scaled to larger areas and applied to support temperature forecasting in different river systems. The framework also represents a successful implementation of a model web approach that uses open standards and web services to integrate complex models from different domains, and which applies these models to generate operational forecasts required to address an important ecological management challenge.

## Acknowledgment

The authors would like to thank W. Turner and G. Geller for their support and guidance on this project.

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